Climate Change Threats to Flying Foxes in Queensland, Australia: A Comprehensive Analysis of Habitat Shifts and Population Declines

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Abstract:

Flying foxes, large flying mammals found in eastern Australia, play a vital role as pollinators and seed dispersers. However, their populations and habitats are under threat due to the increasing frequency of extreme events caused by climate change. This study focuses on investigating the changes in flying fox habitats and populations in Queensland, Australia, between 2007 and 2021 as well as their connection to climate change. Two datasets were used: the Flying-fox Monitoring Program (FMP) dataset, which monitors four flying fox species, and the climate data from the SILO. Data preprocessing involved merging the datasets, removing insufficient observations, and handling missing values through predictive imputation. The data analysis was performed using R Studio, with essential packages for data processing and visualization. The analysis examined habitat changes, climate conditions, and the relationship between extreme hot days and flying fox populations. Geographic visualizations depicted habitat changes, while column plots illustrated climate preferences of different species and the bar plot shows relationships between extreme hot days and the population of flying foxes. The results indicate an increasing number of roosts and a northward movement of flying foxes over the study period. The population of flying foxes exhibited a significant decline, particularly the little red flying fox. The population decline in certain regions correlated with an increase in the number of hot days. The benefit of this study is understanding the influence of climate change on flying fox populations and habitats. It will help us build proactive measures to maintain the long-term sustainability of Australian plantation and the ecological balance of the ecosystem.

1. Introduction:

Flying foxes are large flying mammals found in eastern Australia. Although they are the natural reservoirs of many deadly viruses (Wynne & Wang, 2013), as large and active night pollinators, flying foxes are able to carry large and heavy seeds to parent plants over long distances to maintain the health of Australian plantations (Pierson & Rainey, 1992). In recent years, the increased frequency of extreme events due to climate change such as droughts, heatwaves, and floods has threatened many terrestrial species(Shivanna, 2022), including the flying fox in Australia. The study observed that bushfires are directly connected to the increasing flying-fox mortalities in summer (Mo et al., 2022). This study aims to investigate the changes in the flying fox habitat and population in Queensland, Australia between 2007 and 2021. By examining climate indicators, we are looking to determine if these habitat and population changes have a connection to climate change. The outcome of this study can provide insight to policymakers and industries about the importance of implementing measures to address climate change and protect flying foxes in Australia.

2. Data:

Data Description

Two individual datasets were included in this study. The Flying-fox Monitoring Program (FMP) (Department of Environment and Science, 2022) is the main dataset for investigate the flying fox, and the climate data is supporting dataset provide relative climate indicators.

FMP is conducted by the Queensland Department of Environment and Science (DES). Data is collected from known roosts which is also called camp in Queensland by Local Government Authorities. All roosts data were reported quarterly between March 2003 and March 2022. The FMP is monitoring four flying fox species across Queensland which include the black flying-fox, the grey head flying-fox, the little red flying-fox and the spectacle flying-fox.
The climate data was extracted from SILO database (SILO, 2023) between January 2003 to March 2022. It includes a range of climate variables such as maximum temperature, rainfall, and relative humidity by daily observation. The extracted mothed was using the exact match gridded data according to the 454 known roosts' geographic coordinates (Longitude and Latitude) from the FMP Camp list. In this study, we investigated four climate variables which are maximum daily temperatures, minimum daily temperatures, relative humidity at maximum temperature and relative humidity at minimum temperature.

Data Pre-processing

Two individual datasets were merged into one single data frame by geographic coordinates and date. We excluded observations from 2003 to 2006 and 2022 due to insufficient observations. Furthermore, a report shows that the spectacle flying-fox is endangered in Australia (TSSC, 2019) which could be why the FMP dataset contains 80% of missing data in the spectacle flying-fox variable. Therefore, we removed it from our study.
Two outliers were found, they could be typing errors with an additional 'zero' at the end; however, we consider them as missing values to avoid attribute interventions. 192 missing values were also found from three species. Therefore, the total missing value is 194. The records of flying foxes could be affected by location and month of years. Hence, a predictive imputation was applied to handle the missing values.
As a result, we have totally 15 years of data which contains 11288 observations. *Table 1* gives the data frame of 14 variables related to our investigation.

Table 1: Variable information of the Date Frame

Variable Name	Description	Data type	Variable Type
lga	Local Government Authority	Character	Nominal
Camp	Name of Camp	Character	Nominal
Latitude	Latitude	Double	Continuous
Longitude	Longitude	Double	Continuous
Date	Date	Date	Ordinal
FF.abs	Flying Fox Absent	Binary	Discrete
bbf	Black flying fox	Integer	Discrete
ghff	Grey head flying fox	Integer	Discrete
lrff	Little red flying fox	Integer	Discrete
tff	Total numbers of flying foxes	Integer	Discrete
T.Max	Maximum temperature	Double	Continuous
T.Min	Minimum temperature	Double	Continuous
RHmaxT	Relative Humidity at maximum temperature	Double	Continuous
RHminT	Relative Humidity at minimum temperature	Double	Continuous

3. Methods

3.1 Software

R Studio (Posit team, 2023) was used in this study for data analysis, essential packages are including tidyr (Wickham, Vaughan, et al., 2023) and dplyr (Wickham, François, et al., 2023) for data processing, and ggplot2(Wickham, 2016) for visualisation.

3.2 Data Processing

Import Data

We imported multiple data files using two ***for loops*** and stored the data into two separate lists. Within the loops, we applied the ***select*** function to choose variables for our analysis. Afterwards, we used the ***rbindlist*** function from the ***data.table*** *(Dowle, 2023)* package to combine the data from the lists into two dataframes: one for flying foxes monitoring raw data and another for climate data raw data. We then used the ***leftjoin*** function to merge the two dataframes based on the ***Latitude***, ***Longitude***, and ***Date*** variables, creating the main dataframe for our analysis.

Clean Data

To ensure data quality, we applied the ***gsub*** function to replace or remove any undesired substrings from character data. Subsequently, we converted the cleaned data into the appropriate data types using functions like ***as.Date*** and ***as.numeric***.

Missing Data Imputation

To handle missing data, we employed predictive imputation. Firstly, we built a simple linear model using the ***lm*** function, considering three predictors: ***Longitude***, ***Latitude***, and ***Month***. The ***Longitude*** and ***Latitude*** variables are known to be highly correlated with the number of flying foxes detected, while the ***Month*** variable can potentially represent seasonal behaviour. We used the ***format*** function to extract the month from the ***Date*** variable for each observation. Next, we used the ***predict*** function to generate prediction values and applied them to the missing values using the ***mutate*** function.

3.3 Data analysis

Gather Variables

We used the ***gather*** function to combine all species into a single column named ***Species*** and their corresponding value as ***Number***. Subsequently we also needed to remove the column containing the total number of flying foxes. We assigned it a new dataframe to keep our original dataframe intact. Then, we created a new categorical variable representing three five-year-periods using the ***mutate*** function.

Data Visualisation

The entire visualisation process was using ***ggplot***.

The first goal is to understand the habitat changes of flying foxes in Queensland. To achieve this, we require the ***ozmap*** package *(Sumner, 2021)***.** The ***geom_sf*** is used to plot geographic coordinate's location data. The ***coord_sf*** allows us to specify coordinate systems. The ***facet_grid*** is used to divide the periods into different plots. We employed ***geom_point*** to shows locations of flying foxes, using the aesthetic mappings of ***color*** to represent species and ***size*** to indicate numbers.

The second goal is to understand the climate conditions in which flying foxes are commonly found. To achieve this, we converted the temperature and humidity variables into integers using ***as.integer***. Then, we generated two column plots using the ***geom_col*** function. Each plot uses ***facet_grid*** to divide the three species. Each column in the plot represents a 1°C or 1%RH interval.

The final goal is to understand the relationship between extreme hot day and the population of flying foxes, we considered the max temperature greater than 36 °C as an extreme hot day. We used the ***summarise*** function along with ***arrange*** to identify the top 10 regions with the highest total numbers of flying foxes. Subsequently, we filtered the dataset to select these regions and used ***group_by*** and ***summarise*** to calculate the total numbers of flying foxes in each region for each year. Similar regional data extraction was performed on the climate data dataset. Finally, we plotted two bar plots to compare and gain insights.

4 Results and Discussion

4. 1 Results

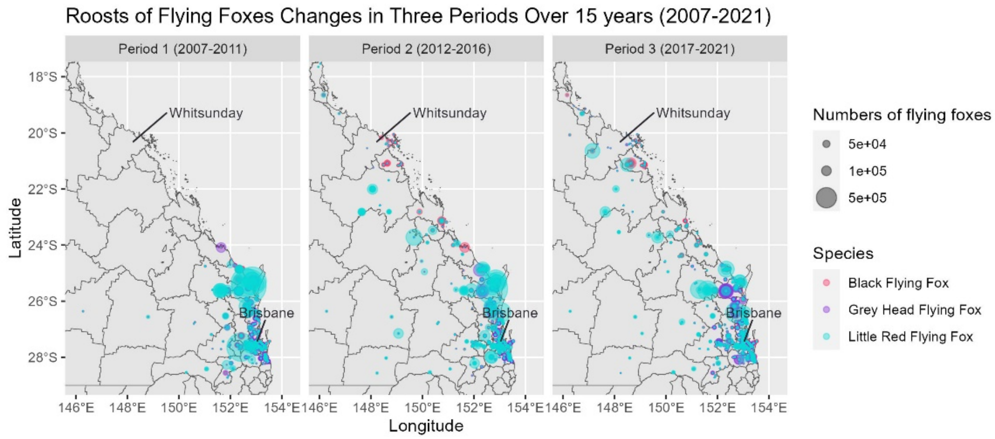

Figure 1 The Map shows the location of three flying fox species were observed across different time spans.

Figure 1 shows the habitat changes of flying fox from 2007 to 2021, we observed an increasing of roosts during these periods, as well as a trend of movement towards to north region. In particular, the little red flying fox is spreading widely. *Table 2* shows the statistical changes during these three periods. The total numbers of roosts has increased, while the population shows a downward trend, with the population of little red flying fox decreasing by half.

Table 2 Statistics for three flying foxes species were observed in different time periods

Species	Year by Group	Total Numbers of Roosts	Total Number of Flying foxes
Black Flying Fox	Period 1 (2007-2011)	163	7327445
	Period 2 (2012-2016)	220	4253770
	Period 3 (2017-2021)	307	4971993
Grey Head Flying Fox	Period 1 (2007-2011)	140	5712922
	Period 2 (2012-2016)	163	4534768
	Period 3 (2017-2021)	228	5467258
Little Red Flying Fox	Period 1 (2007-2011)	87	10912496
	Period 2 (2012-2016)	131	8682428
	Period 3 (2017-2021)	172	6184334

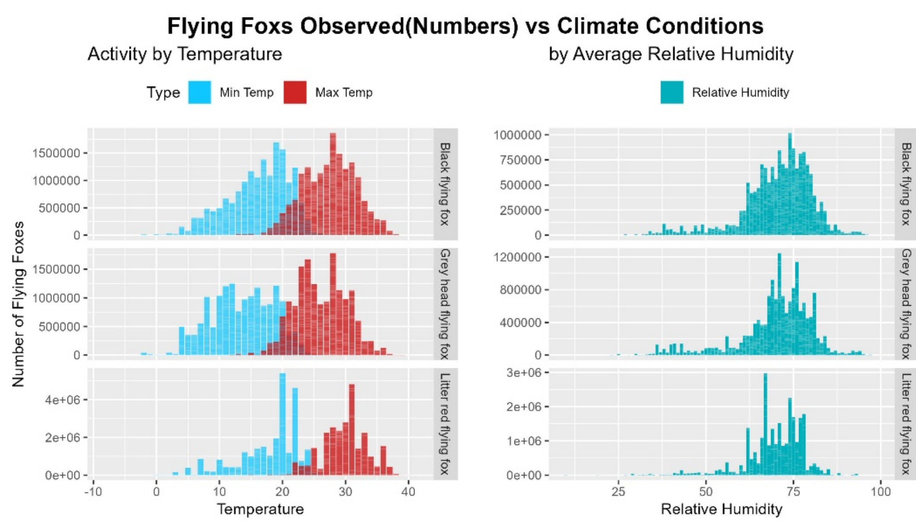

Figure 2 The living environment climate data of three species of flying foxes

Figure 2 shows that the black flying fox and the grey head flying fox have a similar temperature and humidity preference. However, the little red flying foxes seems more fastidious about the habitat. In comparison to the other two species, little red flying foxes prefer warmer and less humid. This might explain their habitat locations have been spreading quickly over the last 15 years as shown in *Figure 1*.

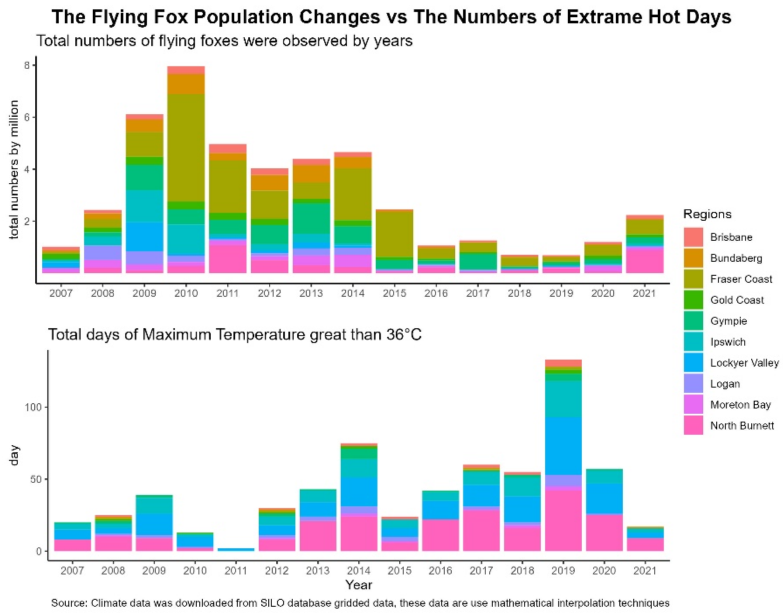

Figure 3 Bar plots of Top 10 Flying foxes activity region

Figure 3 provides a comparison of the population changes of flying foxes by year and the total number of days with temperatures exceeding 36°C each year in the top 10 flying fox population regions. These regions are located in southeast Queensland. We can observe a negative relationship between the number of recorded hot days and the population of flying foxes in these areas. Specifically, some regions, such as Ipswich and Lockyer Valley, have hardly observed flying foxes since 2014.

4.2 Discussion

Our analysis shows that three species flying foxes are leaving their original habitat and searching for new places. Additionally, the total population of flying foxes is decreasing in Queensland. The trend may be attributed to two factors. Firstly, flying foxes finding new roosts as the old one is unsuitable to live anymore, the new one might not yet be recognized or out of the FMP's observational scope. Secondly, the increased mortality rate of the flying foxes due to extreme weather events. The reduction in flying fox populations can have detrimental effects on Australian plantations and further contribute to climate change, creating a negative feedback loop.

5. Conclusion

The findings of this analysis underscore the influence of climate change on flying fox populations and habitats. We found a negative relationship between the population of the flying foxes and extreme hot days. Additionally, we observed that flying foxes are migrating away from Southeast Queensland, which is the most active area for flying foxes in Queensland. However, our study has certain limitations, such as focusing only on climate factors, a limited area, and timeframe. Future studies can be conducted in other states of Australia and explore potential confounding factors, such as habitat loss, disease outbreaks, or human activities.

All in all, protecting flying foxes and their habitats is crucial. Proactive measures are needed to address climate change and mitigate its impact on flying foxes. These measures can contribute to the long-term sustainability of Australian plantations and the maintenance of the ecological balance in our ecosystem.

Reference

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Required Packages

```
library(dplyr)
library(ggplot2)
library(ggpubr)
library(tidyr)
library(data.table)
```

Data Pre-Processing

Import flying fox raw data

```
## Reading Raw Data
file_contents <- list()  # Temporary list for place reading data
for (i in 1:25){
  file_name <- paste0("Flying fox raw data/flyingfox (", i, ").csv")
  file_contents[[i]] <- read.csv(file_name)
}                         # Reading total 25 files
for (i in seq_along(file_contents)) {
  cat("Data Frame", i, ":\n")
  print(colnames(file_contents[[i]]))
  print(length(file_contents[[i]]))
  cat("\n")
}                         # Check colnames of all datasets
```

Combine flying foxes raw data

```
## Data cleaning
flyingfoxs_ls <- list()  # A list for store require data
name = c("lga", "Camp", "Latitude", "Longitude", "Date",
         "FF.abs", "bff", "ghff", "lrff", "sff", "tff")   # Name for all new datasets

for(i in 1:25){
  flyingfoxs_ls[[i]] <- select(file_contents[[i]],
                               -contains("id"),-contains("distribution"), -matches("Time"))
  colnames(flyingfoxs_ls[[i]]) <- name
}           # select required variable and rename all colnames to same

flyingfoxs <- rbindlist(flyingfoxs_ls) %>%  # Row bind all dateframes
              filter(!is.na(Latitude))      # remove 20 empty rows
```

Cleaning flyingfox data

```
## Variables
flyingfoxs$Date <- as.Date(substr(flyingfoxs$Date,
                                  1, 10),  # Sub select string from 1 to 10
                           format = "%Y-%m-%d")  # Convert it to Date type
flyingfoxs <- flyingfoxs %>%
  mutate(Latitude = as.numeric(gsub("^'", "",  # Remove the first character if it is a single quote # Latitude
                                    Latitude)))  # Latitude as numeric
flyingfoxs <- flyingfoxs %>%
  mutate(Longitude = as.numeric(gsub("^3", "",  # Remove a typos start with 3
                                     Longitude)
                                ))              # Longitude as numeric
flyingfoxs$lga[flyingfoxs$lga == "Baloone"] = "Balonne"   # Typos modify
flyingfoxs$lga[flyingfoxs$lga == "gympie"] = "Gympie"    # Typos modify
```

Import climate data

```
## Merge Climate data to the data set
files <- list.files(path ="./climate_data",
                    pattern = "*.txt")# Get the list of file names

climate_raw_data <- list()   # Create an empty list to store the data frames
for (file in files) {        # Loop through each file and read the CSV
  filepath <- paste("./climate_data/",
                    file, sep = "")   # Get the full file path
  data <- read.csv(filepath)          # Read data "txt file"
  climate_raw_data[[file]] <- data %>%
    select(Date,                      # Select required variables
           T.Max, T.Min,
           RHmaxT,RHminT,
           Latitude, Longitude)       # Add all data frame to the list
  }
climate_data <- rbindlist(climate_raw_data)   # combine raw data to one dataset
climate_data <- climate_data %>%
  mutate(Date = as.Date(as.character(Date),
                        format = "%Y%m%d"))  # transfer Date to Date format
```

Combine climate data with fliying fox data

```
## Dateset for analysis
fly_climate <- left_join(flyingfoxs,          # main dataset
                         climate_data,        # support dataset for climate
                         by = c("Date","Latitude", "Longitude")) # conditions

fly_climate <- select(fly_climate,
                      -sff)      # Remove spectacle flying fox due to data unavailable

fly_climate$lrff[fly_climate$lrff == 2500000] = NA # outlier to NA
fly_climate$bff[fly_climate$bff == 750000] = NA  # outlier to NA

fly_climate <- fly_climate %>%
  filter(Date > '2007-01-01' & Date < '2022-01-01')  # select year > 2007
```

Handling missing data

```
## predictive imputation

fly_climate$month <- format(fly_climate$Date,"%m") # New variable month for prediction

bff_pre <- filter(fly_climate, is.na(bff))         # missing bff
bff_mod <- filter(fly_climate, !(is.na(bff)))      # no missing bff
model_bff <- lm(bff
            ~ Latitude + Longitude + month,        # predictors
            data = bff_mod
            )
fly_climate <- mutate(fly_climate,
                      bff = ifelse(is.na(bff),
                                   ifelse(FF.abs == 0,predict(model_bff, bff_pre),
                                          0),bff)) # apply to missing value


ghff_pre <- filter(fly_climate, is.na(ghff))       #  missing ghff
ghff_mod <- filter(fly_climate, !(is.na(ghff)))    # no missing ghff
model_ghff <- lm(ghff
            ~ Latitude + Longitude + month,        # predictors
            data = ghff_mod
            )

fly_climate <- mutate(fly_climate,
                      ghff = ifelse(is.na(ghff),
                                   ifelse(FF.abs == 0,predict(model_ghff, ghff_pre),
                                          0),ghff))         # apply to missing value


lrff_pre <- filter(fly_climate, is.na(lrff))      #  missing lrff
lrff_mod <- filter(fly_climate, !(is.na(lrff)))   # no missing lrff
model_lrff <- lm(lrff
            ~ Latitude + Longitude + month,       # predictors
            data = lrff_mod
            )
predict(model_lrff, lrff_pre)
fly_climate <- mutate(fly_climate,
                      lrff = ifelse(is.na(lrff),ifelse(FF.abs == 0,
                                          ifelse(predict(model_lrff, lrff_pre)>0,
                                                 predict(model_lrff, lrff_pre),
                                                 0),0),lrff)) # apply to missing value

fly_climate <- mutate(fly_climate,
                      tff = ghff + bff + lrff)   # recalculate total number
fly_climate <- fly_climate %>% select(-month)    # Remove month
```

Reshape data

```
fly_climate$year <- format(as.Date(fly_climate$Date),"%Y") # new variable year

fly_climate <- fly_climate %>%
  mutate(RHavg = (RHmaxT + RHminT)/2) %>%   # Add average RH as RHavg
  select(-c(RHmaxT, RHminT))                # Remove RHmaxT and RHminT


fly_climate_gat <- fly_climate %>%
  select(-tff) %>%                          # remove tff
  gather(`bff`, `ghff`, `lrff`,
         key = "Species",
         value = "number")                  # combine 3 speices together
```

```
fly_climate_gat <- fly_climate_gat %>%
  mutate(year_g = ifelse(year < 2012 & year > 2007,
                       "Period 1 (2007-2011)",
                       ifelse(year < 2017 & year > 2012,
                              "Period 2 (2012-2016)",
                              "Period 3 (2017-2021)"))
         )                                # New categorical variable for years
```

Data Analysis

Investigate data

```
fly_climate_gat %>% group_by(year) %>%
  summarise(total_camp = n_distinct(Camp)) # number of camps by year

fly_climate_gat %>%   # number of camps by Species and 3 periods
  filter(number>0) %>%
  group_by(Species, year_g ) %>%
  summarise(total_camp = n_distinct(Camp),
            total_number = sum(number))
```

Roost Locations

```
library(ozmaps)

require("ggrepel")
loc_info <- data.frame(lga = c("Brisbane", "Whitsunday"),
                   Latitude = c(-27.4705,  -20.3441 ),
                   Longitude = c(153.0260,  148.1893 )) # label two regions

ggplot(fly_climate_gat) +
  geom_sf(data = ozmaps::abs_lga,
        show.legend = FALSE) +
  geom_point(aes(x = Longitude, y = Latitude,
               size = number, color = Species),
             alpha = 0.4) +
  coord_sf(xlim = c(146, 154.3),            # limit of geocor system
           ylim = c(-28.8, -18)) +
  scale_size_area(breaks = c(5e+4, 1e+5, 5e+5),
                  max_size = 10,
                  name = "Counts of flying foxes") +
  scale_color_manual(values = c(bff = "#FF2E63", lrff = "#08D9D6", ghff = "#892CDC"),
                     labels = c("Black Flying Fox",
                                "Grey Head Flying Fox",
                                "Little Red Flying Fox")) +
  geom_text_repel(data = loc_info,          # Display Brisban and Whitsunday
                  aes(x=Longitude, y=Latitude,
                      group=lga, label=lga),
                  size = 3.2, hjust=-0.5, vjust=-2.5,
                  color = "#2B2730") +
  labs(title = "Number of flying foxes change in three period in 15 years (2007-2021)") +
  facet_grid(~ year_g)
```

Habitat Conditions

```
fly_climate_gat$T.Max <- as.integer(fly_climate_gat$T.Max)  # Transfer T.Max to Integer
fly_climate_gat$T.Min <- as.integer(fly_climate_gat$T.Min)  # Transfer T.Min to Integer

# Temp plot
fig.1 <- fly_climate_gat %>%  ggplot() +
  geom_col(aes(x = T.Min, y = number, fill = "Min Temp"), alpha = 0.7) +
  geom_col(aes(x = T.Max, y = number, fill = "Max Temp"), alpha = 0.8) +
  scale_fill_manual(values = c("Min Temp"= "#00C4FF","Max Temp"= "#CD1818"),
                    name = "Type",
                    breaks = c("Min Temp", "Max Temp", "Relative Humidity")) +
  facet_grid(Species ~., scales = "free",
             labeller = labeller(Species = c(bff = "Black flying fox",
                                             ghff = "Grey head flying fox",
                                             lrff = "Litter red flying fox"))) +
   labs(title = "Activity by Temperature", x = "Temperature", y = "Number of Flying Foxes",
        color = "Temperature type") +
  theme(legend.position = "top")


fly_climate_gat$RHavg <- as.integer(fly_climate_gat$RHavg) # Transfer RHavg to Integer

# Humidity
```

```r
fig.2 <- ggplot(fly_climate_gat) +
  geom_col(aes(x = RHavg, y = number,
               fill = "Relative Humidity")) +
  scale_fill_manual(values = c("Relative Humidity" = "#00AFBB"),
                    aesthetics = c("color", "fill"), name = "") +
  labs(title = "by Average Relative Humidity",
       x = "Relative Humidity",
       y = "") +
  theme(legend.position = "top") +
  facet_grid(Species ~., scales = "free",
             labeller = labeller(Species = c(bff = "Black flying fox",
                                             ghff = "Grey head flying fox",
                                             lrff = "Litter red flying fox")))

  annotate_figure(ggarrange(fig.1, fig.2, ncol = 2, nrow = 1), top = text_grob("Flying Foxs Observed(Numbers) vs Climate C
onditions",
               color = "black", face = "bold", size = 16))
```

Hot Days vs Population

```r
lga_top_10 <- (fly_climate %>%
                 group_by(lga) %>%
                 summarise(total = sum(tff)) %>%
                 arrange(desc(total))
               )[1:10,]   # find top 10 total

fly_climate_top_10 <- fly_climate %>%
  filter(lga %in% unlist(lga_top_10)) %>%
  group_by(lga, year) %>%
  summarise(Total = sum(tff))  # filter out  from fly_climate


## top 10 area of total flying foxs
fig.fox <- ggplot(data = fly_climate_top_10,
                aes(x = year, y = Total, fill = lga)) +
  geom_col() +
  theme_classic() +
  labs(title = "Total numbers of flying foxes were observed by years",
       x = "", y = "total numbers by million", fill = "Regions") +
  scale_y_continuous(breaks = c(2e+6, 4e+6, 6e+6, 8e+6),
                    labels = c(2,4,6,8))

## investigate climate data
climate_data$year <- format(as.Date(climate_data$Date),"%Y")  # create a year column

lga_loc_ls <- fly_climate %>%
  group_by(lga, Latitude, Longitude) %>%
  summarise(total = sum(tff))         # Create look up lists for lga

climate_data_0 <- left_join(filter(climate_data,
                                   year < 2022 & year > 2006),
                            lga_loc_ls,
                            by =c('Latitude', 'Longitude')
                            )       # climate_data_for investigate max temperature
t.max.day <- climate_data_0 %>%
  group_by(lga, year, Date) %>%
  summarise(T.Max = mean(T.Max))                # mean T.max by days

fig.tem <- t.max.day %>%
  group_by(year, lga) %>%
  summarise(day = sum(T.Max>36)) %>%
  filter(lga %in% unlist(lga_top_10)) %>%
  ggplot() +
  geom_col(aes(x = year, y = day, fill = lga)) +
  theme_classic()+
  labs(title = "Total days of Maximum Temperature great than 36°C",
       caption  = "Source: Climate data was downloaded from SILO database gridded data, these data are use mathematical in
terpolation techniques",
       x = "Year",
       y = "day",
       fill = "Regions")

annotate_figure(ggarrange(fig.fox, fig.tem , ncol = 1, nrow = 2, common.legend = TRUE, legend = "right"), top = text_grob(
"The Flying Fox Population Changes vs The Numbers of Extrame Hot Days ",
               color = "black", face = "bold", size = 16))
```